A Multi-objective Approach to Indoor Wireless Heterogeneous Networks Planning

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***Abstract*—We present a multi-objective optimization approach for indoor wireless network planning subject to constraints for exposure minimization, coverage maximization and power consumption minimization. We consider heterogeneous networks consisting of WiFi Access Points (APs) and Long Term Evolution (LTE) femtocells. We propose a design framework based on Multi-objective Biogeography-based Optimization (MOBBO). The results of the proposed method indicate the advantages and applicability of the multi-objective approach.**

***Index Terms*— Indoor wireless network planning, heterogeneous networks, exposure minimization, biogeography-based optimization, Pareto optimization, multi-objective optimization.**

I. INTRODUCTION

Wireless network design problems are in general multi-objective. Common design objectives include exposure minimization, coverage maximization, power consumption minimization and cost reduction [1-6]. Multi-objective Evolutionary Algorithms (MOEAs), which mimic behaviour of biological entities, are suitable optimization techniques for solving the above-described problem.

Biogeography-based optimization (BBO) [7] is a recently introduced evolutionary algorithm, which is based on mathematical models that describe how species migrate from one island to another, how new species arise, and how species become extinct. The way the problem solution is found is analogous to nature's way of distributing species. In the BBO approach there is a way of sharing information between solutions [7], similar to the other evolutionary algorithms. Additionally, BBO has some unique features, which are different from those found in the other evolutionary algorithms. These differences can make BBO outperform other algorithms [7].

In this paper, we use a multi-objective extension of the BBO algorithm (MOBBO) combined with the concept of non-dominated ranking found in Nondominated Sorting Genetic Algorithm-II NSGA-II [8]. Therefore, we apply both the above-mentioned multi-objective evolutionary algorithms to the heterogeneous wireless network planning problem. With heterogeneous, we mean a combination of different wireless technologies, namely WiFi APs and Long-Term Evolution (LTE) femtocells. We define this problem as one with three objective functions. We consider an objective function for exposure minimization, coverage maximization, and power consumption minimization. The advantages of our approach are clearly shown for multi-objective network planning problems.

II. PROBLEM DEFINITION

We consider the ground plan of an office building in Ghent, Belgium to which the network planning optimization will be applied (Fig. 1). It is a 90 m (length) by 17 m (width) office environment. The red circles indicate points that do not require coverage (e.g. toilets, elevator shafts and kitchens). The wall material is layered drywall indicated in Fig.1 with brown lines, while the gray lines indicate concrete.

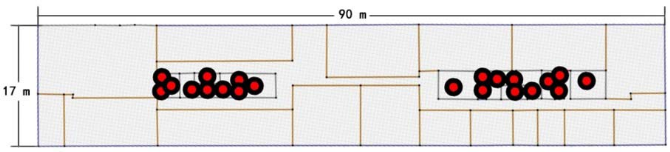


Fig. 1. Map of the ground plan the office building where the network planning is applied.

WiFi (IEEE 802.11n) access points at 2.4 GHz and LTE base stations at 2.6 GHz will be installed at a subset of 425 possible locations in the building. The assumed receiver antenna gain is 0 dBi and a received power of −68 dBm is required to obtain a capacity of 54 Mbps. There are also 425 receiver location for which coverage and exposure level will be calculated. The PL will be modeled according to two-slope model proposed by the IEEE 802.11 TGn channel models group [9].

The network-planning problem is to find the AP characteristics (position and Equivalent Isotropically Radiated Power (EIRP)) in such a way that the power consumption is minimized, the human exposure to electric fields is minimized, and the coverage is maximized. All the above objectives are subject to constraints regarding coverage and exposure limits. Furthermore, since we consider a heterogeneous network, at least one LTE femtocell should be present. The coverage requirement depends on the capacity in Mbps and therefore on the receiver sensitivity that is required in each case.

Such a problem is inherently multi-objective. It can be defined by the minimization of the objective functions given below:

$f_1(\overline{x}) = N_{AP}^{on}$ minimize power consumption (1)

$f_2(\overline{x}) = -100 \times \dfrac{C_{sol}(\overline{x})}{C_{tot}(\overline{x})}$ maximize coverage (2)

$f_3(\overline{x}) = E_{median}(\overline{x})$ minimize exposure (3)

subject to:

$g_1(\overline{x}) = |f_2(\overline{x})| \geq C_{limit}$ coverage limit (4)

$g_2(\overline{x}) = f_3(\overline{x}) \leq E_{limit}$ exposure limit (5)

$g_3(\overline{x}) = N_{LTE}^{on} \geq 1$ at least one LTE femtocell is present(6)

where N_{AP}^{on} is the total number of base stations (both LTE and WiFi) that is turned on, N_{LTE}^{on} the number of turned on LTE femtocells, C_{limit} the coverage percentage required (0-100), E_{limit} the desired electric-field maximum median value (V/m), E_{median} the calculated electric field median value (V/m), C_{sol} is the number of reception points covered by the current solution in this indoor environment, and C_{tot} is the total number of all reception points in the building floor.

The above-mentioned problem can be solved using a multi-objective evolutionary algorithm. It is an integer-programming problem, for which several different solutions exist.

III. Biogeography-based Optimization (BBO)

The mathematical models of Biogeography are based on the work of Robert MacArthur and Edward Wilson in the early 1960s. Using this model, they have been able to predict the number of species in a habitat. The habitat is an area that is geographically isolated from other habitats. The geographical areas that are well suited as residences for biological species are said to have a high habitat suitability index (HSI). Therefore, every habitat is characterized by the HSI which depends on factors like rainfall, diversity of vegetation, diversity of topographic features, land area, and temperature. Each of the features that characterize habitability is known as suitability index variables (SIV). The SIVs are the independent variables while HSI is the dependent variable.

Therefore, a solution to a D-dimensional problem can be represented as a vector of SIV variables $[SIV_1, SIV_2, ...SIV_D]$, which is a habitat or island. The value of HSI of a habitat is the value of the objective function that corresponds to that solution and it is found by

$$HSI = F(habitat) = F(SIV_1, SIV_2, ...SIV_D) \quad (7)$$

Habitats with a high HSI are good solutions of the objective function, while poor solutions are those habitats with a low HSI. The habitats with high HSI are those that have large population and high emigration rate μ. For these habitats, the immigration rate λ is low. The immigration and emigration rates are functions of the number of species in the habitats. These are given by

$$\mu_k = E\left(\frac{k}{S_{\max}}\right) \quad (8)$$

$$\lambda_k = I\left(1 - \frac{k}{S_{\max}}\right) \quad (9)$$

where I is the maximum possible immigration rate, E is the maximum possible emigration rate, k is the number of species of the k-th individual, and $S_{\max}$ is maximum number of species. BBO uses both mutation and migration operators. The application of these operators to each SIV in each solution is decided probabilistically. The mutation rate m of a solution S is defined to be inversely proportional to the solution probability and it is given by

$$m(S) = m_{\max}\left(\frac{1 - P_s}{P_{\max}}\right) \quad (10)$$

where P_s is the probability that a habitat contains S species and $m_{\max}$ is a user-defined parameter. More details about the BBO algorithm can be found in [7, 10].

A. *Multi-objective Biogeography-based Optimization (MOBBO)*

Multi-objective BBO algorithms extend the original BBO algorithm for solving MOOP. The results found by an evolutionary algorithm are also called Pareto set approximation or approximation set. MOBBO is the hybridization between BBO and uses concepts common in other MO algorithms like NSGA-II. The MOBBO algorithm is outlined below:

1) Initialize the BBO control parameters. Map the problem solutions to SIVs and habitats. Set the habitat modification probability P_{mod}, the maximum immigration rate *I*, the maximum emigration rate *E*, the maximum migration rate $m_{\max}$ and the elitism parameter *p* (if elitism is desired).

2) Initialize a random population of NP habitats (solutions) from a uniform distribution. Set the number of generations *G* to one.

3) Evaluate objective function and constraint function values.

4) Apply non-dominated ranking to *NP* habitats. Compute (HSI) for each habitat of the population based on non-dominated ranking.

5) Map the HSI value to the number of species *S*, the immigration rate λ_k, the emigration rate μ_k for each solution of the population.

6) Generate a new child population of NP habitats, which is originally the same as the parent population.

7) Apply the migration operator for each member of the child population based on immigration and emigration rates using (8) and (9).

8) Update the species count probability using

$$\dot{P}_s = \begin{cases} -(\lambda_s + \mu_s) P_s + \mu_{s+1} P_{s+1} + \lambda_{s-1} P_{s-1} & S < S_{\max} \\ -(\lambda_s + \mu_s) P_s + \lambda_{s-1} P_{s-1} & S = S_{\max} \end{cases} \quad (11)$$

where $\dot{P}_s$ is the species count probability matrix.

9) Apply the mutation operator to each member of the child population according to (10).

10) Evaluate objective function and constraint function values.

11) Merge original parent population with new child population to form a population 2*NP* habitats.

12) Apply non-dominated ranking to 2*NP* habitats. Select NP non-dominated habitats, which are the new parent population. The non-dominated ranking refers to sorting of the vectors regarding non-domination. This sorting approach is called Fast Non-dominated Sorting Approach and is described in detail in [8].

13) Repeat step 5 until the maximum number of generations $G_{\max}$ is reached.

To decrease the population back to the original size a sorting technique is applied. This uses the concept of Crowding Distance (CD), which approximates the crowdedness of a vector in its non-dominated set like NSGA-II [8].

IV. Numerical Results

We consider 425 different possible AP positions placed at a height 200 cm above ground level and the receiver is assumed at a height 100 cm above ground level (Fig. 1). WiFi Aps and LTE femtocells have different EIRP values. Therefore, the total number of the optimization variables is 850. The first 425 variables could have a value of 0 (no AP turned on), 1 (WiFi AP turned on), or 2 (LTE femtocell turned on). The range of the possible EIRP values is from 0 to 20 dBm (100 mW) for both the WiFi and the LTE APs. We will compare the results from three different network planning design cases. The cases will be for High Definition (HD) video coverage, and Standard Definition (SD) video coverage. We compare MOBBO with NSGA-II. The algorithms are executed 20 times. The best results are compared. Both algorithms are initialized with a population size of 200 and run for 1000 iterations.

In order to choose the best-compromised solution from the Pareto Front a suitable decision maker has to be used. The fuzzy set theory has been used as a decision maker in several applications in the literature like transportation planning, vendor selection, etc. [11, 12]. The satisfaction degree of each objective function is represented by a linear fuzzy membership function expressed as

$$\mu_k = \begin{cases} 1 \;\; if \;\; z_k \le z_k^{\min} \\ \dfrac{z_k^{\max} - z_k}{z_k^{\max} - z_k^{\min}} \;\; if \;\; z_k^{\min} < z_k < z_k^{\max} \\ 0 \;\; if \;\; z_k \ge z_k^{\max} \end{cases} \quad (12)$$

where z_k the value of k-th objective function, $z_k^{\min}$, $z_k^{\max}$ are the minimum and maximum value of the k-th objective function respectively. The best-compromised solution is found by using

$$s = \frac{1}{n_{obj}} \sum_{k=1}^{n_{obj}} \mu_k \quad (13)$$

where n_{obj} is the number of objectives and s is the degree of satisfaction.

For each Pareto Front point, we calculate the value of *s*. The point with the maximum s value is the best-compromised solution.

The first example is that of case 1, which assumes High Definition (HD) video coverage (receiver sensitivity set to -68 dBm and -68.1 dBm for WiFi and LTE respectively) for all points with coverage limit $C_{limit} = 99\%, E_{limit} = 0.25 \; V/m$. The exposure limit is low in order to test the algorithms' performance on demanding cases. The 3D Pareto fronts for this case found by both algorithms are shown in Fig. 2 and Fig. 3 respectively. Each point of the Pareto front denotes a feasible network configuration. We notice that NSGA-II obtained Pareto fronts with a larger number of APs than MOBBO. The tradeoff for this case is the lower electric field values.

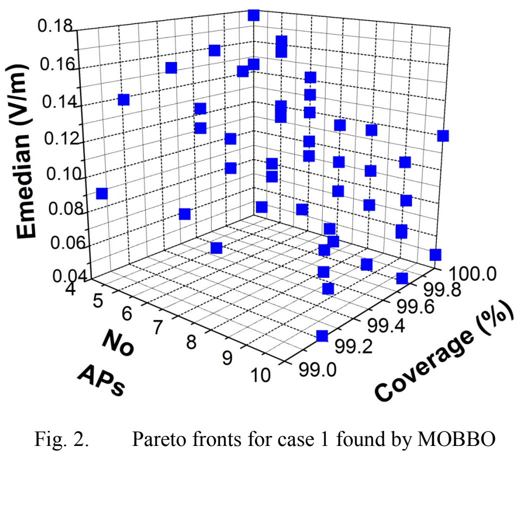


Fig. 2. Pareto fronts for case 1 found by MOBBO

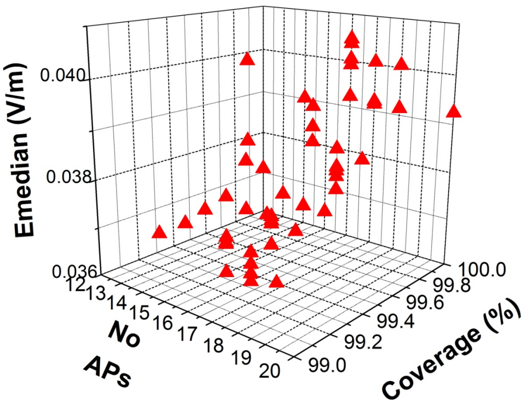


Fig. 3. Pareto fronts for case 1 found by NSGA-II

The final example presents a network layout where 25Mpbs video (SD) is required for all points. The receiver sensitivity is set to -79 dBm and -77.1 dBm for WiFi and LTE respectively. The constraints for this case are $C_{limit} = 99\%, E_{limit} = 0.1\ V/m$. For this case we assume that a LTE femtocell is always present with EIRP=10 dBm at a specific position. The Pareto fronts found are shown in Fig. 4 and Fig.5. The APs range for MOBBO is from 3 to 7. The NSGA-II for the same exposure and coverage range obtained solutions that range from five to eight.

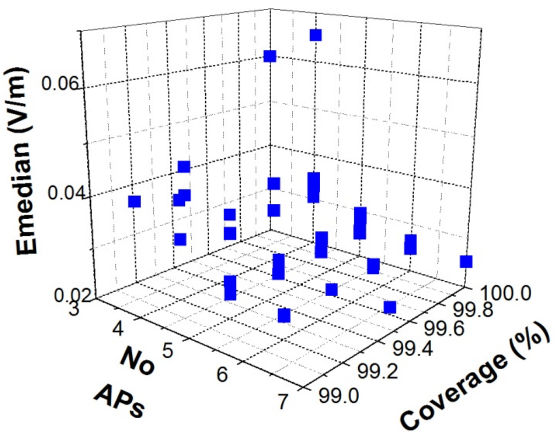
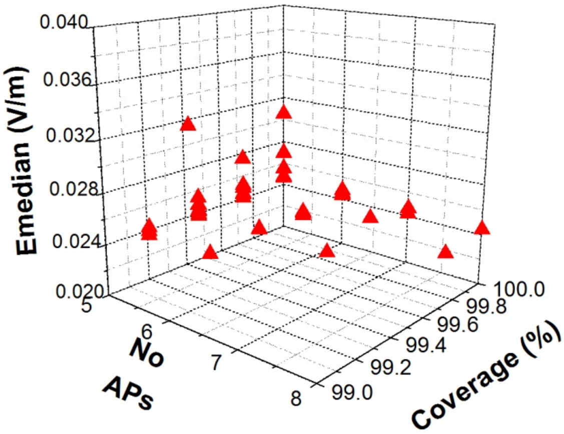


Fig. 4. Pareto fronts for case 2 found by MOBBO



(b)

Fig. 5. Pareto fronts for case 2 found by NSGA-II

TABLE I. BEST COMPROMISED SOLUTIONS

Case 1:HD video coverage $C_{limit} = 99\%, E_{limit} = 0.25V/m$				
Algorithm	**Number of APs**	**Coverage (%)**	**Emedian (V/m)**	**Std. Dev.**
MOBBO	5	100	0.113	0.142
NSGA-II	13	100	0.037	0.045
Case 2:SD video coverage $C_{limit} = 99\%, E_{limit} = 0.1V/m$				
Algorithm	**Number of APs**	**Coverage (%)**	**Emedian (V/m)**	**Std. Dev.**
MOBBO	4	100	0.030	0.058
NSGA-II	6	100	0.024	0.043

Table I reports the best-compromised solutions found by both algorithms in the two cases. We notice that for case 1 MOBBO obtained the solution with the lowest number of APs. The solution found by NSGA-II is that with the lowest electric-field value. The results for case 2 differ. The number of APs is lower than that of the other cases. As could be expected, the lower smartphone (Wifi and LTE) receiver sensitivity results in fewer APs needed. We notice that the solution obtained by MOBBO is the one with the lowest number of APs. The solution obtained by NSGA-II is the one with the lowest exposure value. We notice that the E-field standard deviation values are lower for lower exposure limits. This implies that the E-field distribution is more homogeneous for these cases. We also notice that the solutions obtained by NSGA-II are the ones with the lower standard deviation values. The tradeoff for lower AP number (thus lower power consumption) is higher field exposure values and larger dispersion of E-field values.

The network layout and the E-field distribution for the best configurations obtained by MOBBO is shown in Figs 6a-6b. In case 2 (Fig. 6b), the LTE femtocell (EIRP of 10 dBm) and the WiFi APs are indicated. It is evident that increasing the number of APs results to lower exposure values and more homogeneous E-field distribution.

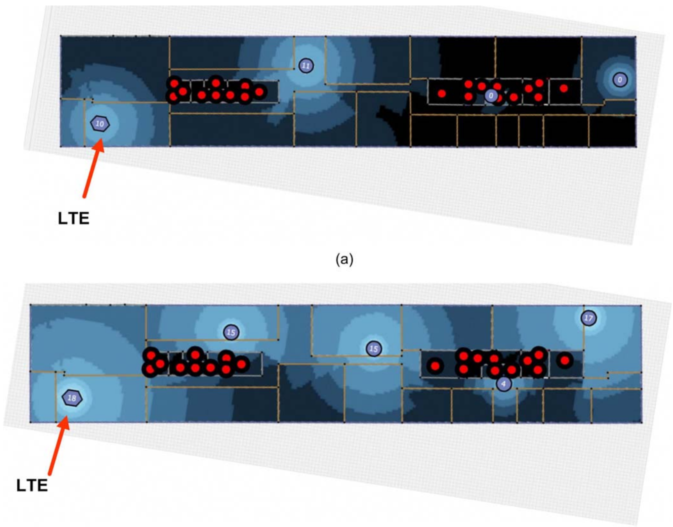


Fig. 6. Network layout of best-compromised solutions found by MOBBO a) Case 1 b) Case 2. (WiFi AP = dot, LTE femtocell = hexagon, EIRP is indicated within dot or hexagon).

V. CONCLUSION

The problem of heterogeneous (LTE and WiFi) network planning for optimal coverage with the lowest power consumption and the lowest exposure is addressed in this paper. An application for a realistic office environment is investigated leading to reductions of cost and exposure when multi-objective algorithms are applied.

We proposed a multi-objective algorithm based on BBO and the concept of non-dominated ranking. MOBBO has been compared against NSGA-II for the network planning problem. MOBBO produces better results than NGSA-II for the same population size and for the same number of generations.

The numerical results obtained by multi-objective algorithms allow the network engineer the possibility of selecting from a set of optimal solutions. All the above algorithms can be easily applied to different network planning problems. In our future work, we intend to examine different network configurations using different constraints.

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